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Current Transformer Saturation Detection with Genetically Optimized Neural Networks

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***Abstract* — Application of the genetic algorithm (GA) for optimization of artificial neural network (ANN) based CT saturation detector is presented. To determine the most suitable ANN topology for the CT state classifier the rules of evolutionary improvement of the characteristics of individuals by concurrence and heredity are used. The proposed genetic optimization principles were implemented in MATLAB programming code. The initial as well as further consecutive network populations were created, trained and graded in a closed loop until the selection criterion was fulfilled. Various aspects of genetic optimization have been studied, including ANN quality assessment, versions of genetic operations etc. The developed optimized neural CT saturation detector has been tested with EMTP-ATP generated signals, proving better performance than traditionally used algorithms and methods.**

***Index Terms* — protective relaying, CT saturation, artificial intelligence, neural networks, genetic algorithms, transient analysis**

I. Introduction

Contemporary protection and control devices or units used in power systems realize their functions nowadays in digital technique. Nevertheless, whatever sophisticated algorithms of signal processing are further used, the overall performance of the protection relay is also a function of quality of the analog signal pre-processing path including current and voltage transformers, analog antialiasing filters and A/D converters. One of the most seriously deteriorating impacts on protection operation may be observed when traditionally used induction-type current transformers become saturated due to high AC fault current and/or DC current components. It is obvious that protection criterion values calculated on the basis of saturated CT secondary signal may fall quite distantly from their correct values, which might have been determined if the CT primary unsaturated signal was available (Fig. 1). Erroneous measurement may in consequence lead to false decisions (e.g. underreaching of overcurrent relays, overestimation of fault loop impedance in distance relays) and protection maloperation. Thus it can be stated that CT saturation phenomenon may impair protection system reliability if appropriate algorithms for saturation detection and/or correction are not applied to eliminate the problem.

Several approaches may be found in the literature to mitigate or eliminate the impact of CT saturation on protection operation. Among others the following are the most valuable:

- determination of CT saturation basing on normative recommendations [1] or CT model equations [2],

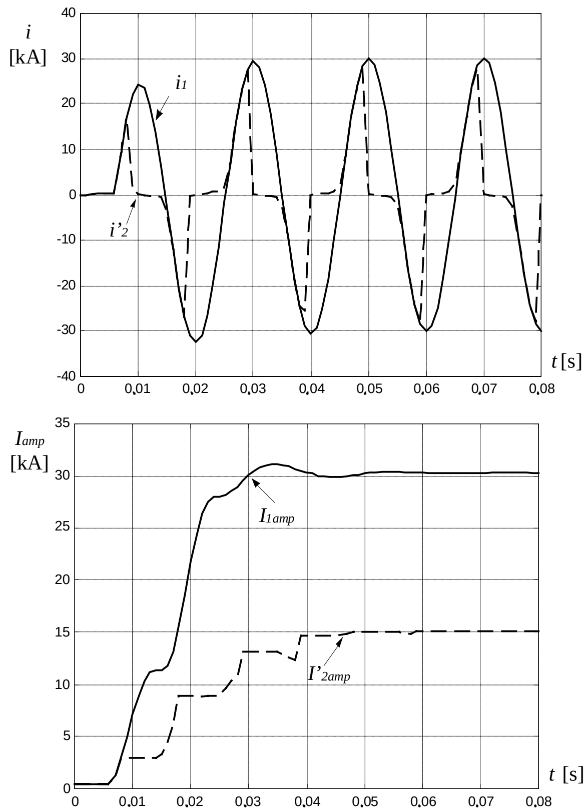

Fig. 1. Primary and secondary CT currents: a) instantaneous signals, b) measured amplitudes (algorithm with full-cycle Fourier filters used).

- detection of CT saturation with use of algorithmic methods (measurement of certain signal features), e.g. [3],
- use of artificial intelligence techniques (including ANNs) for CT saturation detection and compensation, e.g. [4].

In this paper the third approach based on application of neural networks is studied. It has been proved that considerable improvement of operation as well as quite simple achievement of adaptive features of protection functions may be obtained with use of various AI techniques [5]. Artificial neural networks represent a modern approach to problem solving also for power system protection and control applications. Advantages of neural computing methodologies over conventional approaches include faster computation, learning ability, robustness and noise rejection.

While preparing useful and efficient ANN-based classification/recognition unit, one has to take into consideration at least the issues of the ANN choice (structure type, number of layers and neurons, neuron activation functions, input signals) and its training (learning method, initial conditions).

Choosing the type of ANN structure and its further parameters is rather a matter of the designer experiences with ANN usage since, unfortunately, there are no general practical rules that could be applied for that purpose. The heuristic way with sequential trial-and-error attempts may be followed, however, this may not guarantee the optimal ANN structure to be found. Thus, in this paper an optimization approach based on genetic principles is proposed and its efficiency is studied. The following sections of the paper describe the genetic algorithm itself, its application for ANN optimization for CT saturation detection task as well as testing of the new neural detector with ATP-generated signals and comparison of its performance with chosen traditional detection method.

II. Genetic Algorithm

Genetic algorithms are a result of emulation (numerical implementation) of the evolution principles observed in the nature, with particular concern given to natural selection appearing in the population of living beings. The GAs are mainly applied for solving various optimization problems. From the other traditional optimization approaches they are singled out with the following features:

– the GA does not process the problem parameters directly but in a coded form,
– searching for an optimum is performed commencing not from a single starting point but from a certain population of initial guesses,
– the genetic optimization process is controlled by suitably defined goal function,
– probabilistic instead of deterministic selection rules are applied.

In the field of genetic optimization the concepts and definitions borrowed from genetics are exploited, such as:

- *population* – a set of individuals of selected number,
- *individuals* – representatives of the prospective problem solutions given in a coded form (treated also as points in the search universe),
- *chromosomes* (coding chains or sequences) – ordered sequences (vectors) of *genes*,
- *gene* – single element of the *genotype*, and in particular of the chromosome,
- *genotype* (i.o. words – structure) – a set of chromosomes of given individual,
- *phenotype* – a set of values corresponding to given genotype, i.e. its decoded structure.

Natural principles according to the theory of Darwin, such as heredity, crossover, mutation, and selection, are used over several generations to develop and improve the characteristics of the individuals. An important role in GA plays the idea of *adaptation function*, which is also called *matching function* or *goal function*. The adaptation function allows assessing the adaptation grade of each individual in the population, which forms the base for selection of the best individuals, according to the general rule that “only the strongest can survive”.

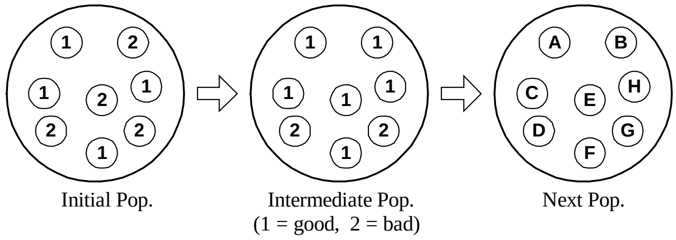

Fig. 2. Basic scheme of the genetic optimization process.

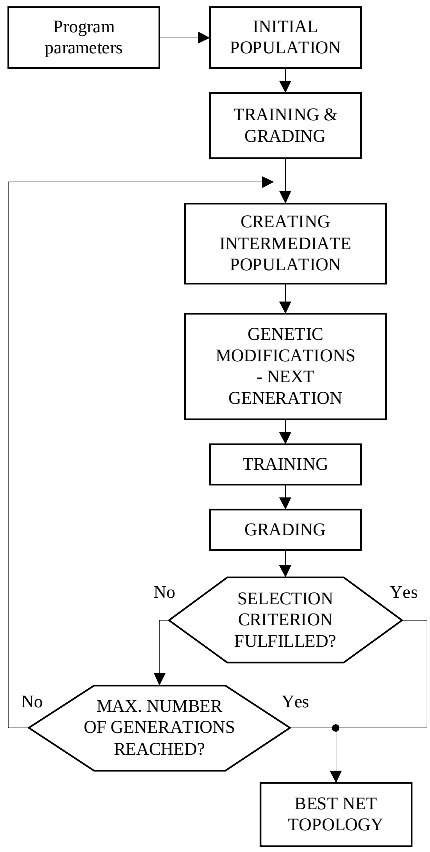

Fig. 3. Flow chart of the GA procedure for the ANN topology optimization.

The block scheme of the basic genetic procedure is presented in Fig. 2. The algorithm starts from creating of the initial population, which can be understood as a random choice of a number of individuals represented by vectors of their encoded parameters (chromosomes). In every iteration of GA the adaptation grade of each individual is assessed, basing on which the new (intermediate) population is established with the best individuals from previous stage being represented more frequently. The members of intermediate population are then subjected to additional genetic modifications and as a result the next population of individuals is created.

Consecutive iterations of GA are called generations, while the new individuals can be treated as offspring (descendants) of elder population. The GA usually runs in a closed loop with the interruption conditions defined according to the specific requirements of the problem to be solved. In optimization analyses the algorithm interruption can occur when preset level of the goal function is reached, if need be – with given accuracy. The GA procedure can also be interrupted when its further operation does not improve the optimization outcomes (no better results are expected). If the GA interruption conditions are satisfied the best chromosome is accepted as final solution. Otherwise the algorithm operation is continued until certain time has passed or the prescribed number of iterations is reached.

In Fig. 3 block scheme of the genetic optimization procedure as applied for ANN structure optimization is presented. At the beginning an initial population of neural networks is randomly created. While the number of neurons in the input and output layer are fixed according to the classification problem, the number of hidden layers and the number of neurons in these layers are randomly selected. The neural networks are trained with selected typical patterns and validated with all available patterns. After the adaptation function of each individual was determined (quality index Q calculated), an intermediate population is created where successful individuals are reproduced more likely. This may be realized with one of following selection algorithms (Fig. 4):

- "wheel of roulette" method (a segment of circle proportional to ANN quality index is assigned to each individual, ANN selection for intermediate population is done by drawing, Fig. 4a),
- "tournament" method (the ANNs are joint in pairs at random, the individuals compete with each other which of the two can introduce its two replicas into the intermediate population, deterministic as well as probabilistic selection is possible, Fig. 4b),
- "ranking place" method (a ranking list according to ANN quality indices is created, intermediate population is composed out of the first half of individuals (top of the ranking list) and their replicas, Fig. 4c).

After selection of ANNs for the intermediate population is done, several genetic operations can be applied to create individuals of the next population. The most important one is the crossover of two parent individuals (Fig. 5) to produce new descendants. Furthermore, mutations can take place, which change the network topology randomly by adding or removing neurons. Mutations are used to avoid that the optimization is done around a local minimum.

The newly created population is trained again and then subjected to quality determination (grading). The consecutive populations of ANNs are created, trained and graded until the optimization criterion is fulfilled. The evolutionary process

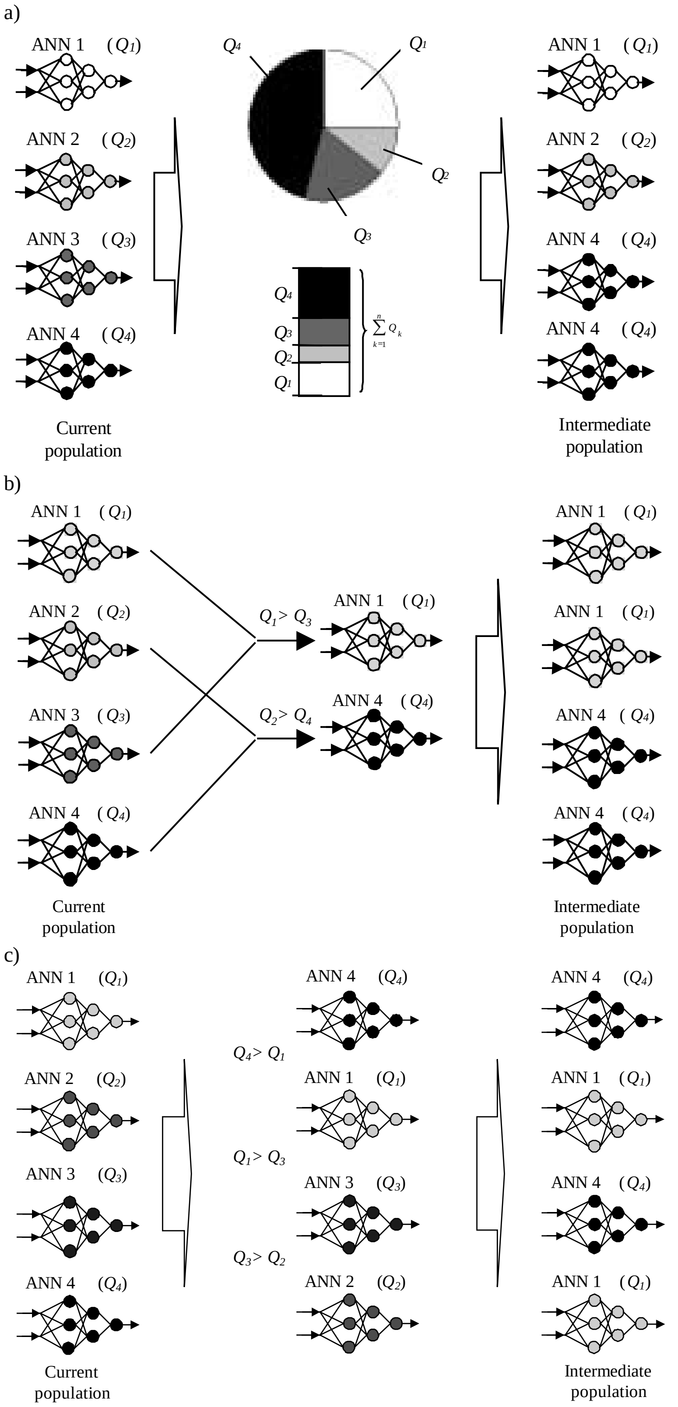

Fig. 4. Illustration of sample selection procedures: a) the "wheel of roulette" method, b) the "tournament" method, c) the "ranking place" method.

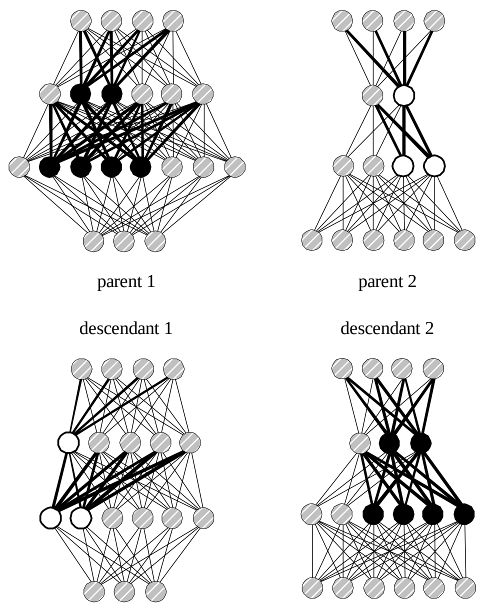

Fig. 5. Crossover of groups of neurons to create new descendent individuals.

described should end up in an optimum that represents the most appropriate neural network topology.

The GA scheme described has been successfully used by the authors in ANN optimization for the generator out-of-step protection decision module [6, 7]. Here, the procedure was applied for optimization of the ANNs for CT saturation detection task. In the next section of the paper the genetic procedure is described with more details and several implementation aspects (crucial for final results) are discussed.

III. Optimization Results and Scheme Testing

A. *GA implementation details*

Optimization of the neural CT saturation detector was performed going out of a population of neural networks consisted of 20 individuals. The ANNs were being trained with the first half and tested with the second half of pattern signals originating from EMTP-ATP simulation of current transformer operation. The ANN input vector consisted of 10 most recent samples of the CT secondary current, which may be seen as signal windowing with 10ms long data window (by sampling frequency f_s=1kHz). The Levenberg-Marquardt training algorithm was adopted with the desired output of the ANN set to 1.0 for the periods of linear CT operation and 0.0 when the CT was saturated.

The dynamic (time instant n dependent) training target function was defined as:

$$T(n)=\begin{cases} 1 \quad when \quad \left|\dfrac{i'_1(n)-i_2(n)}{i'_1(n)}\right| > 0.1 \\ 0 \quad when \quad \left|\dfrac{i'_1(n)-i_2(n)}{i'_1(n)}\right| \le 0.1 \end{cases} \tag{1}$$

which means that CT saturation was confirmed when the relative difference between its primary (related to secondary) and secondary currents was higher than 10% of the CT secondary current at given time instant.

Implementation of the GA procedure brought about results, which, among the others, depend on the definition of the ANN quality index (adaptation function). Two versions of the index were analyzed, i.e. efficiency index Q_{eff} and efficiency/size index $Q_{eff/size}$, according to the formulae

$$Q_{eff}=\frac{number\ of\ correct\ decisions}{number\ of\ all\ testing\ cases} \tag{2}$$

$$Q_{eff\ /\ size}=\frac{1}{(1-Q_{eff})\cdot 2\cdot n_{ANN}} \tag{3}$$

where n_{ANN} stands for ANN size (total number of neurons).

With the quality index (2) the best neural nets from the population considered were assigned values close to 1.0, while the worst ones were graded with values approaching 0.0. One has to understand that the assessment of ANN with use of the efficiency index Q_{eff} is done with respect to the ANN performance quality only (in terms of percentage of correctly classified cases) without taking into consideration the ANN size. Such an approach can sometimes lead to quite big neural networks, implementation of which may create problems if they are going to be applied in on-line operating protection or control systems (high computational burden, proportional to the ANN size). In order to drive the optimization process in both efficiency and ANN size directions the quality index (3) was proposed. The values of $Q_{eff/size}$ (not limited to 1.0) are inversely proportional to the total number of neurons of ANNs being assessed, thus giving a chance of obtaining efficient yet reasonably small (and implementable) neural networks. In first attempt the simple ratio of Q_{eff} to n_{ANN} was considered, however, such a quality index could sometimes provide very small ANNs but of poor classification abilities. After further investigations the $Q_{eff/size}$ index in form of eqn. (3) was adopted. The analyses confirmed that such an approach could lead to much better optimization results in both ANN efficiency and size aspects.

The best ANNs obtained for respective quality indices are:

- for Q_{eff} index – ANN having 14 neurons (13-1), classification efficiency equal 0.978, and
- for $Q_{eff/size}$ index – ANN having 6 neurons (3-2-1), classification efficiency 0.954.

As one can see, optimization with combined index (3) ceased with twice smaller neural network by only slight decrease of ANN classification abilities.

The operation of described genetic optimization algorithm was thoroughly tested taking also into account various ways of selection procedure realization (see Fig. 4) as well as various probability values for occurrence of particular genetic operations. The genetic operations mentioned in previous section were realized with regard to neural networks in the following way:

- crossover operation (with probability p_c) consisted in exchange of some neurons between two ANN individuals; the crossover could concern single neurons (with probability p_{sn}), groups of neurons (p_{gn}) or whole layers (p_l).
- mutation operation (with probability p_m) was realized in one of the following versions: delete a neuron, duplicate a neuron, delete a layer of neurons or duplicate a layer of neurons.

In Table 1 the optimization results of the neural CT detectors are gathered for various selection methods applied and probability values of the genetic operands adopted. Here, the ANNs were being assessed with the efficiency index Q_{eff}. It is seen that the resulting neural networks are characterized by similar effectiveness of CT state identification. The best ANN (Q_{eff}=0.9783) was obtained for the algorithm *Rn4*, i.e. for selection with ranking place method, probability of crossover set low (p_c=0.3) and probability of mutation high (p_m=0.6). Apart from high classification abilities, its important advantage is also quite small size (the considered ANN consisted only of 14 neurons laid out in two layers). Such a compact neural structure can easily be implemented even in on-line operating protection and control systems.

TABLE I. TOPOLOGIES AND QUALITY INDICES OF THE NEURAL CLASSIFIERS OBTAINED WITH THE GA PROCEDURE FOR VARIOUS COMBINATIONS OF SELECTION METHOD AND PROBABILITIES OF GENETIC OPERATIONS.

	Optimization results (best ANN size and quality) for selection process realized with the method of:			
Probability values	Wheel of roulette	Ranking place	Tournament with determi-nistic choice	Tournament with random choice
$p_m = 0.25$ $p_c = 0.65$ (p_l=0.75 p_{gn}=0.20)	ANN-R1: (11-1) Q_{eff} = 0.9637	ANN-Rn1: (14-1) Q_{eff} = 0.9742	ANN-Td1: (5-9-3-1) Q_{eff} = 0.9720	ANN-Tr1: (6-10-1) Q_{eff} = 0.9563
$p_m = 0.25$ $p_c = 0.65$ (p_l=0.40 p_{gn}=0.55)	ANN-R2: (4-11-1) Q_{eff} = 0.9707	ANN-Rn2: (6-15-1) Q_{eff} = 0.9720	ANN-Td2: (11-8-8-1) Q_{eff} = 0.9670	ANN-Tr2: (11-11-4-4-1) Q_{eff} = 0.9683
$p_m = 0.60$ $p_c = 0.30$ (p_l=0.75 p_{gn}=0.20)	ANN-R3: (6-7-7-1) Q_{eff} = 0.9720	ANN-Rn3: (7-11-12-1) Q_{eff} = 0.9733	ANN-Td3: (9-6-1) Q_{eff} = 0.9650	ANN-Tr3: (9-11-4-1) Q_{eff} = 0.9574
$p_m = 0.60$ $p_c = 0.30$ (p_l=0.40 p_{gn}=0.55)	ANN-R4: (4-8-7-7-1) Q_{eff} = 0.9653	ANN-Rn4: (13-1) Q_{eff} = 0.9783	ANN-Td4: (15-3-11-5-1) Q_{eff} = 0.9723	ANN-Tr4: (6-2-1) Q_{eff} = 0.9687

From Table I one can also draw some conclusions with regard to the influence of the selection method applied on the results of GA operation. Independently of the values of probabilities of genetic operations, the selection method based on “ranking place” approach brought about the ANNs with the highest values of efficiency index Q_{eff}. With this respect the worst one turned out to be the “tournament” selection algorithm with random choice of individuals.

The analysis of results gathered in Table I with respect to influence of the probabilities of genetic operations reveals the fact that the best optimization results are obtained for the algorithms with probability of mutation p_m set higher than probability of crossover p_c. It is also advantageous when the probability of crossover for group of neurons p_{gn} is higher than for the whole layers p_l. Not going into detail it is worth to mention that the probability values do not have to be constant during the run of GA. Usually the value of p_c is higher at the beginning of the optimization process and decreases with time to the advantage of probability p_m, which becomes higher for later generations.

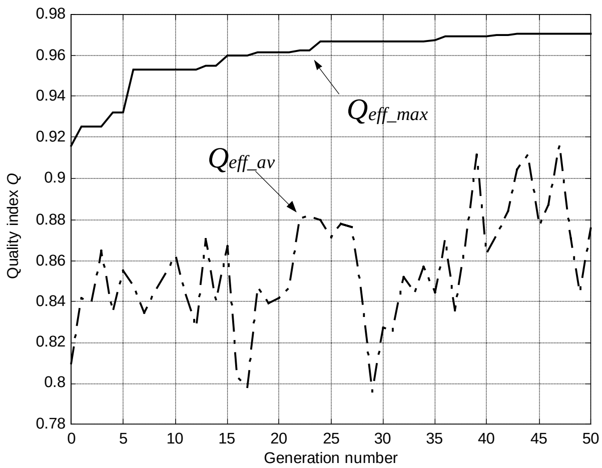

Fig. 6. Optimization process for the algorithm R2 (see Table 1).

In Fig. 6 the course of quality index Q_{eff} during the run of GA algorithm (version with “wheel of roulette” selection method R2) is shown. Looking at the curve of quality index for the best ANN in current population (Q_{eff_max}) one can find that the process convergence is the fastest for the first few iterations. After several generations the pace of optimization decreases and from ca. 25th generation no significant improvement of the neural classifiers is observed. The average quality index (Q_{eff_av}) calculated for the entire population of ANNs is not a monotonic function, however it increases slowly with time, which means that consecutive populations of nets consist of individuals on average better and better adapted for the task they are trained to.

The research performed included also an attempt of ANN structure design with heuristic “trial and error” approach. A number of 1000 neural networks were randomly created, trained and then tested with EMTP-ATP simulation signals. It allowed getting the neural classifiers with 94% efficiency at the most, which is less than obtained with the genetic optimization approach, independently of the selection method and probabilities of genetic operations.

B. CT saturation detector testing and comparative analysis

The developed ANN based CT saturation detection scheme has been thoroughly tested with ATP-generated test signals. In Fig. 7 its response (network ANN-R2, Table I) to sample CT currents is shown. The CT becomes saturated either due to high content of decaying DC component (Fig. 7a) or as an effect of high AC current amplitude (Fig. 7b). In both cases the time periods of current transformer non-linear operation are properly detected (cross line in Fig. 7). It is worth to mention that the currents shown in Fig. 7 belong to the group of testing cases, i.e. they were not shown to the neural networks during training. CT saturation intervals in all of the simulation cases prepared were properly identified, independently of the saturation depth, sometimes only with slight time delay (1-2 sampling periods). The ANN performance index Q_{eff} (Table I) is therefore to be understood as a value related to classification decisions taken sample by sample.

An example of comparison of the developed ANN detector with chosen deterministic CT saturation identification scheme based on calculation of the 3rd derivative of CT secondary current [3] is shown in Fig. 8. It can be seen that, despite of small size of the ANN applied (ANN-R2), all starting and ending points of CT saturation intervals are properly detected. In addition, no unnecessary excitations are observed at the beginning of fault, which takes place when a non-AI method is applied (Fig. 8c). The latter feature of the “classic” method is an effect of the fact that the method responds with high peaks in 3rd derivative to any sudden change in current waveform. The method can react properly (with visible impulses) at the beginning of saturation, but may have problems with detecting saturation endings, when the CT turns to unsaturated operation mode with much smoother waveform change.

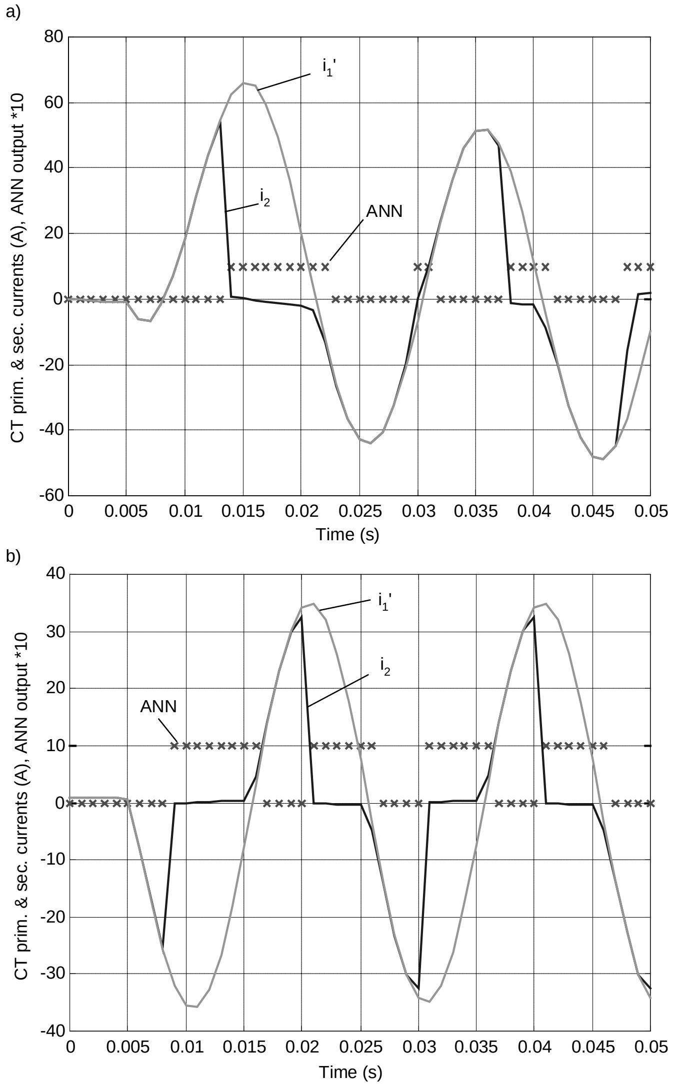

Fig. 7. ANN response for two cases of CT saturation: a) current with high content of decaying DC component, b) high AC current amplitude.

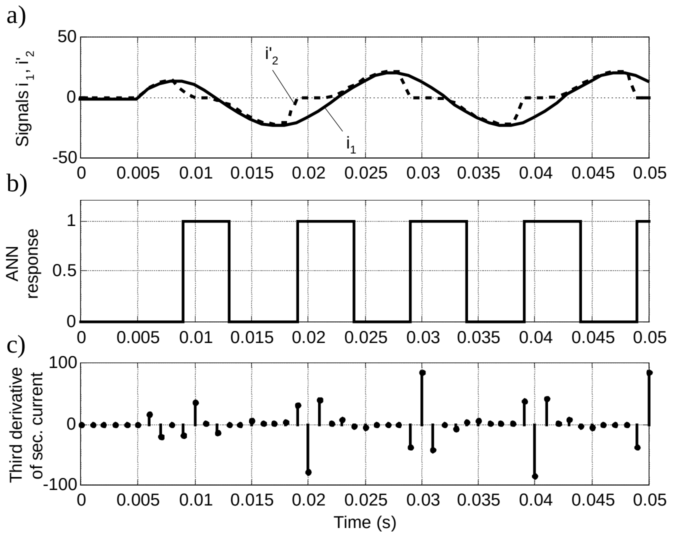

Fig. 8. Comparison of the CT detection approaches: a) CT signals, b) ANN detector response, c) third derivative of CT secondary current.

IV. Conclusions

Possibility of genetic algorithm application for ANN based CT saturation detector optimization is presented and the impact of selection procedure, probabilities of genetic operations and ANN quality assessment indices is discussed. High classification efficiency, good sensitivity, reliability and immunity to noises characterize the saturation detectors designed. It is shown that application of GA optimization approach allows obtaining neural classifiers more or much more efficient than the schemes designed with heuristic "trial and error" method. It has been proved that with appropriate choice of quality assessment method resulting ANNs may have quite compact structures (consisting just of a few neurons), which is important for their possible real-time implementation.

In closing it should be stressed that the rules of genetic optimization described in the paper have a general, universal character and may be used for solving any particular optimization problem.

V. Acknowledgements

The authors would like to thank the Ministry of Science and Information Society Technologies, Poland, for financial support of the research conducted (project No. 3T10B03726).

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VII. Biographies

Waldemar Rebizant (M'2000) was born in Wrocław, Poland, in 1966. He received his M.Sc., Ph.D. (both with honors) as well as D.Sc. degrees from Wroclaw University of Technology, Poland in 1991, 1995 and 2004, respectively. Since 1991 he has been a faculty member of Electrical Engineering Faculty at the WUT. In June 1996 he was awarded Siemens Promotion Prize for the best dissertation in electrical engineering in Poland in 1995. In 1999 he was granted a prestigious Humboldt research scholarship for the academic year 1999/2000. In the scope of his research interests are: digital signal processing and artificial intelligence for power system protection purposes.

Daniel Bejmert (Non-member) was born in 1979 in Wałbrzych, Poland. He graduated from the Faculty of Electrical Engineering of Wroclaw University of Technology, Poland in 2004. At present he is a PhD student at the Institute of Electrical Power Engineering of WUT. His research interests include application of intelligent algorithms in digital protection and control systems.